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Convergence of Crowdsourcing Ideas: A Cognitive Load perspective

Short Paper

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Abstract

Many organizations use crowdsourcing for problem solving, innovation, and consultation. In open innovation and community crowdsourcing initiatives the volume of generated ideas may prevent a careful evaluation if each individual contribution. To overcome this challenge, crowd workers can perform a convergence activity. Convergence involves reducing a large set of ideas to a focused subset of ideas that are worthy of further consideration. While convergence is a critical process for situations were large volumes of ideas must be processed, little is known what affects convergence quality and satisfaction with the convergence process and outcomes. We propose an experimental study that adopts Cognitive Load Theory as its theoretical lens to investigate the effects of task complexity, idea presentation, and instructional guidance on convergence quality and satisfaction. This study has the potential to further our understanding of convergence processes in crowdsourcing and inform the design and guidance of crowdsourcing initiatives.

Keywords*: Open innovation, community crowdsourcing, idea convergence, cognitive load theory, intrinsic cognitive load, extraneous cognitive load, germane cognitive load, task complexity, idea presentation, instructional guidance*

Introduction

Crowdsourcing has become a well-accepted organizational strategy that enables firms to seek creative and transactional assistance beyond their organizational boundaries. Instead of gathering contributions from internal employees, crowdsourcing uses interactive online technologies that provide companies with a cost effective way to invite external actors to contribute to their problem solving, innovation, and consultation processes (Afuah and Tucci, 2013). Common types of crowdsourcing include online labor markets, open innovation contests, collaborative communities, and crowd complementors (e.g. Boudreau and Lakhani, 2013). We focus specifically on forms of crowdsourcing that can be labeled 'idea crowdsourcing' such as open innovation and community crowdsourcing, where an organizer gathers ideas from a crowd and aims to identify the best contributions (Nguyen, et al., 2015).

Past idea crowdsourcing research has focused on different perspectives, including participant motivation (Majchrzak and Malhotra, 2013), incentive mechanisms (Liu et al., 2014), task design (Deng et al., 2016), and value capture (Afuah and Tucci, 2013). Specifically in the context of open innovation and community crowdsourcing, existing studies have focused on idea generation from the perspectives of idea quantity and idea creativity (Bayus, 2013), on different idea generation strategies (Wooten and Ulrich, 2016), and on idea evaluation (Blohm et al., 2016; Girotra et al., 2010). Notwithstanding the contributions of research to date, challenges concerning the idea evaluation and selection process in crowdsourcing initiatives remain. For example, Girotra and colleagues (2010) noted that the final results often do not include the best ideas.

One source for the challenges with idea evaluation and selection is the high number of ideas that can be generated in these crowdsourcing efforts. When processing a large number of submitted ideas, individuals concerned with evaluation and selection are likely to experience cognitive overload (Blohm et al., 2013). To address this challenge, researchers argue to include a convergence phase in the process so that an initial shortlist of most promising contributions is established (Briggs et al., 2003; Merz et al., 2016; Seeber et al., 2015). Our research aims to contribute to our understanding of convergence by using a cognitive load perspective to theorize and test the effects of different ways in which the convergence task can be executed on the quality of convergence outcomes and participant satisfaction. Such an understanding is relevant for the productive organization of open innovation and community crowdsourcing beyond idea generation by the crowd. Specifically, we propose a laboratory experiment to study interventions that are hypothesized to influence three types of cognitive load and consequently impact idea convergence quality and satisfaction.

Research background

During a process of convergence, individuals, teams, or crowds identify ideas that they deem worthy of further attention (Briggs et al. 2003; Seeber et al. 2015, 2016). Research shows that idea convergence can be more time-consuming and challenging than idea generation (Girotra et al., 2010; Hengst & Adkins, 2007), especially when individual judges or panels are confronted with a large volume of ideas. In such situations, the required effort may well exceed the judges' cognitive capabilities. They may experience cognitive overload, which may hurt the quality of the resulting convergence output. It may also lead to frustration and dissatisfaction. Feelings of dissatisfaction can lead to abandonment of crowdsourcing efforts (Bhattacherjee 2001; Briggs et al. 2008). It is thus important from both a quality perspective and sustained use perspective to understand the cognitive load challenges in convergence processes.

Cognitive load theory (CLT) assumes that human cognition is bound by the limitations of working memory, a limited capacity cognitive system used to maintain and manipulate information (Pass et al., 2004). Cognitive load is the total amount of mental effort used in working memory (Cheon and Grant, 2012; Pass et al., 2004). Cognitive overload occurs when the information provided exceeds an individual's working memory capacity.

CLT distinguishes between three types of cognitive load: intrinsic cognitive load, extraneous cognitive load and germane cognitive load (Paas et al., 2004). *Intrinsic* cognitive load is the interaction of individual characteristics and task complexity. Prior knowledge and cognitive capabilities influence individuals' perceptions of the difficulty level on the tasks as well as the task execution process. *Extraneous* cognitive load relates to how information is presented. Extraneous cognitive load increases when information or tasks are presented inadequately or poorly. High levels of intrinsic and extraneous cognitive load may cause cognitive overload if they leave too little working memory capacity available. *Germane* cognitive load concerns supportive designs and procedures that aid the processing, construction, and automation of schemas. A schema is a knowledge framework that represents a class of things, events, and situations (Kolfschoten et al., 2011). In the long-term memory, schemas are repositories of information that are interlinked. If someone does not have proper schemas or if the clues in the information insufficiently activate their schemas, an idea cannot be fully understood and processed.

Initially CLT was most frequently used in the domain of educational psychology to investigate cognitive processes and instructional design. For example, spoken text and visual cues were found to improve learning results with less mental effort (Tabbers et al., 2004). Chen & Wu (2015) demonstrated an increase in cognitive load due to the split-attention when working with separate presentations of multiple information sources. Other researchers found in the context of mobile learning that when different sources of information must be processed simultaneously, replicated information increases cognitive load (Liu et al., 2012). For most studies, natural complexity, element interactivity, and task environment were controlled as the sources of intrinsic cognitive load.

Educational psychology researchers also use CLT to propose and test strategies that promote schema development in long-term memory while easing the intrinsic and extraneous demands on working memory to improve learning complex tasks (Tabbers et al., 2004). The principle behind such strategies is that task performance will improve by removing unnecessary intrinsic and extraneous load that is not required for schema construction. This focus in CLT makes it suitable for studies in the IS domain as well. For example, Vijayasarathy & Casterella (2016) studied the effect of query formulation approaches on cognitive load and showed that the use of SQL query templates improved task performance with more complex queries. Some researchers combine CLT with other theories, such as cognitive fit theory in systems design (Dang et al., 2012) and competition for attention theory in e-commerce (Hong et al., 2004). Other researchers incorporate cognitive load into their research models to understand individuals' cognition (Javadi et al., 2013) or illustrate their findings using CLT (Potter & Balthazard, 2004).

Hypothesis development

Following the logic of CLT, high levels of cognitive effort and corresponding cognitive load are likely to inhibit the idea convergence process. Below, we develop our hypotheses concerning the types of cognitive load and their effect on convergence quality and satisfaction.

Intrinsic cognitive load and task complexity

Task constitutes high level of intrinsic cognitive load when information processing relies on an interaction of multiple elements (Ngu et al., 2014). Intrinsic cognitive load is the inherent level of difficulty associated with a specific task. High task complexity requires more cognitive costs to maintain elements in working memory (Campbell, 1988). The interaction of task complexity and individual capability determines the extent of perceived intrinsic cognitive load (Pass et al., 2004).

Task complexity has long been regarded as an important indicator for information processing performance. One possible explanation is that individuals tend to focus on attentional cues if the task is difficult, thus neglect the cues for the task itself, and lead towards the degradation of task performance (Gupta et al., 2013). This is also supported by empirical studies that found negative correlations of task complexity and performance (Dang et al., 2012; Vijayasarathy & Casterella, 2016). We hypothesize that this relationship is mediated by intrinsic cognitive load. Thus:

Hypothesis 1a: Higher task complexity will lead to higher intrinsic cognitive load.

Hypothesis 1b: Higher intrinsic cognitive load will lead to lower convergence quality.

Hypothesis 1c: Intrinsic cognitive load will partially mediate the relationship between task complexity and convergence quality.

Studies have provided mixed results regarding intrinsic cognitive load and satisfaction. In general, providing subjects with a challenging task may lead to higher levels of satisfaction. For example, subjects in Bradford's (2011) study on online learning experiences reported higher levels of satisfaction when they experienced some challenge in the task. However, if the required amount of cognitive processing goes beyond a threshold, it appears to negatively impact. Huang (2011) found in an online game that subjects reported lower satisfaction levels when they felt overwhelmed with their challenges. In the context of our study, we start from a fundamentally challenging task – processing a considerable number of crowdsourced ideas. Thus we hypothesize:

Hypothesis 1d: Higher intrinsic cognitive load will lead to lower satisfaction.

Hypothesis 1e: Intrinsic cognitive load will partially mediate the relationship between task complexity and satisfaction.

Extraneous cognitive load and idea presentation

Inadequate design occupies working memory capacity but it is irrelevant to schema construction. Thus, extraneous cognitive load increases when information is poorly presented (Pass et al., 2004). Previous research in psychology has proposed two ways of presenting ideas to decrease extraneous cognitive load: methods regarding sensory processing (use dual coding of narration and visual information to control extraneous load) and methods regarding information characteristics (integrate resources and avoid unnecessary materials) (DeLeeuw and Mayer, 2008). For example, in the context of information graphics, spatial contiguity and signaling principle were validated to reduce extraneous cognitive load, which is reflected through the observation of eye movement behavior. Spatial contiguity refers to the physical integration of information sources, while signaling principle relates to highlighting cues that attract attention (Holsanova et al., 2009).

According to competition for attention theory, layout and organization of information may impact the distance from the area of focal attention. For example, physical salience of objects such as the neat formatting and distinctive sizes easily attract attention, and leads to better search performance (Hong et al., 2004). Researchers further found that attention cues, such as using arrows, colors, or highlighting, reduce extraneous cognitive load associated with locating relevant information, and lead to better performance (De Koning et al., 2009). Considering previous empirical support for the negative effect of extraneous cognitive load on decision quality (Varshney, 2014) and learning performance (Chen & Wu, 2015), we posit that extraneous cognitive load also has a negative effect on convergence quality. Furthermore, studies in E-commerce and distance education have found that higher levels of extraneous cognitive load are associated with lower reported levels of satisfaction (Miller, 2011; Schmutz, 2009). Thus:

Hypothesis 2a: Higher idea presentation quality will lead to lower extraneous cognitive load.

Hypothesis 2b: Higher extraneous cognitive load will lead to lower convergence quality.

Hypothesis 2c: Extraneous cognitive load will partially mediate the relationship between idea presentation quality and convergence quality.

Hypothesis 2d: Higher extraneous cognitive load will lead to lower satisfaction.

Hypothesis 2e: Extraneous cognitive load will partially mediate the relationship between idea presentation quality and satisfaction.

Germane cognitive load and instructional guidance

Individuals often overlook possible considerations result from their limitations of working memory (Santanen et al., 2004), therefore, stimuli, such as instructional guidance is helpful to stimulate and guide participants to engage in schema construction, automation and activation and in this way increase germane cognitive load (Ayres & Pass, 2007). Germane cognitive load is a positive load related with schema formulation and automation. Several instructional interventions can be used to increase germane cognitive load (Paas et al., 2004). Researchers proposed several recommendations to form germane cognitive load, such as redirecting attention, explanatory feedback (Moreno, 2004), instructional explanations, and worked examples (Pass and Van, 2006). External process facilitation and activity intervention were found to contribute to the formation of germane cognitive load (Van Gog et al., 2005). According to schema theory and script theory of guidance, interventions like instructional guidance offer individuals efficient ways to process information. People will perform their tasks in a more structured way by taking shortcuts in interpreting the vast amount of information through specific guidance. When instructional guidance is provided, information processing schema will be generated and can be retrieved more easily (Fischer et al., 2013; Axelrod, 1973).

The broader the range of schema available in long term memory and the easier they are accessible, the more information can be processed, the faster one can learn to find solutions to problems and the better outcome one will achieve (Kolfschoten et al., 2011). Thus, we argue that an increase in germane cognitive load leads to better idea convergence outcomes in the idea crowdsourcing context. Further, we argue that when someone can process information more easily and achieve better outcomes, (s)he will also experience a higher level of satisfaction. Thus, we posit the following relationships between instructional guidance, germane cognitive load, convergence quality, and satisfaction:

Hypothesis 3a: Instructional guidance will lead to higher germane cognitive load.
Hypothesis 3b: Higher germane cognitive load will lead to higher convergence quality.
Hypothesis 3c: Germane cognitive load will partially mediate the relationship between instructional guidance and convergence quality.
Hypothesis 3d: Higher germane cognitive load will lead to higher satisfaction.
Hypothesis 3e: Germane cognitive load will partially mediate the relationship between instructional guidance and satisfaction.

The resulting research model is presented in figure 1.

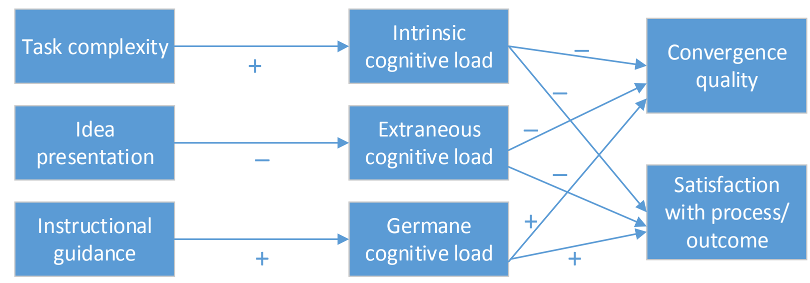

Figure 1. Modified Research Model

Method

We will employ a 2x2x2 factorial design. The three independent variables manipulated in the experiment are task complexity (high vs. low), idea presentation (good presentation vs. poor presentation) and instructional guidance (guidance vs. no guidance). After completing their experimental task, participants will answer a questionnaire to measure demographics and perceptions regarding satisfaction and cognitive load types.

Participants

To ensure a statistical power of 0.8 (as recommended by Baroudi & Orlikowski (1989)), the sample size for the study is 264 people, corresponding to 33 people in each of the 8 treatments. This sample size is based on the output of GPower, a statistical software tool for a priori power analysis (Faul et al., 2007), with the input values as 0.80 for statistical power (1-β), 0.05 for statistical significance (α), 0.40 for effect size (d), and 8 for the number of treatment groups (corresponding to 7 degrees of freedom). We will recruit undergraduate student, who will receive course credit for participation. Subjects will be randomly assigned to the eight treatment conditions. Subjects will perform the convergence task in ThinkTank, an online collaboration application that supports idea crowdsourcing.

Task and procedure

The idea convergence task concerns innovations in electronic commerce (EC) settings. We collected 100 ideas from an idea sharing website for solving problems regarding Cross-border E-commerce website and business development. Subjects will be asked to shortlist 10 ideas that they perceive worthy of further consideration to be included in a final set of recommendations. Subjects will be instructed to include ideas that are relevant to the topic, that are elaborated on a useful level of detail, and that do not overlap with other ideas in their shortlist.

Measures

Independent variables

We manipulate task complexity by the numbers of ideas assigned to low and high task complexity conditions. In high task complexity conditions, subject must process twice the numbers of ideas than the low task complexity conditions (100 vs. 50) within a fixed timeframe.

We manipulate idea presentation in two ways. First, drawing on the work of Coleman & Liu (1975) and Blohm et al. (2016), high presentation conditions will have better idea readability in the starting list than low presentation conditions. To determine readability, we use the Coleman–Liau index ($CLI = 0.0588L - 0.296S - 15.8$ where L is the average number of letters per 100 words and S is the average number of sentences per 100 words). Second, in the high presentation conditions we will format ideas, highlight keywords, and organize them into categories. In low presentation conditions, ideas are presented in a simple long list.

Lastly, detailed scripts will be given to the high instructional guidance conditions. Subject will receive a suggested procedure to process and select ideas. Specifically, they will be guided to first sort ideas into three quality levels (high, medium, low) and then finalize the high category to reach their top 10 shortlist. Examples of high, medium and low ideas will be presented to the subjects in guidance groups. The low guidance condition will only receive the instruction to select the 10 most promising ideas.

After the experiment, we will collect subjects' perceptions on task complexity, idea presentation and instructional guidance as the manipulation check.

Cognitive load

Researchers have proposed three types of techniques to measure cognitive load: subjective rating scales, physiological measures, and secondary tasks (DeLeeuw & Mayer, 2008). In our study, we adopt a combination of these three techniques. Subjective ratings will be adopted to measure intrinsic, extraneous and germane cognitive load respectively (Chang et al., 2017; Cheon & Grant, 2012). Extraneous cognitive load can be measured through fixation count and time count using eye-tracking (Holsanova et al., 2009). We will use an opensource webcam-based eye-tracking application (Papoutsaki et al., 2016).

Control variables

We will control the demographic features (Age, gender, past experience) , as well as individual capability of the subjects involved in the experiment, and include three additional control variables. To measure individual task capability, a secondary task will be performed prior to the experiment task: we designed a video game where subjects have to pick the unique shape among a bunch of graphic patterns under time constraints to test their information processing capabilities. A subject's task capability is represented by their game score.

We will measure knowledge self-efficacy as a control variable to assess the subjects' confidence towards their idea convergence task using an adaptation of the scales by Lin (2006) and Vreede (2016). We will measure emotional valence and arousal to evaluate the influence of emotional state on individuals' working memory capacity allocation using functional magnetic resonance imaging (fMRI). We will measure need for cognition to assess individuals' inherent intention to follow the guidelines using an adaption of the scales by Tam and Ho (2005).

Dependent variables

The two dependent variables are convergence quality and satisfaction. We adopt the approach from Seeber et al. (2015) to measure convergence quality as the average of task relevance and extent of idea development. An idea is task relevant if it potentially addresses a problem involved in Cross-border E-commerce. Extent of idea development is the idea's level of detail to clarify the specific solution it describes in terms of the number of dimensions of communicative interaction ('why', 'who', 'how', 'when', 'where', and 'if') that are represented (Yates and Orlikowski 2002). Satisfaction is measured along two dimensions: satisfaction with process and satisfaction outcome. We will use the instrument proposed by Briggs et al. (2013).

Plan of analysis

We will use Structural Equation Modeling (SEM) to examine the relationships between the variables. We use SEM because our research model is a complex model with moderated mediation and SEM allows simultaneous and complete tests of all relationships.

Expected contributions

This research will contribute to our understanding of cognitive processes involved in convergence in idea crowdsourcing. We go beyond existing studies in ideation and idea selection by grounding crowdsourcing convergence process in cognitive load theory, investigating the differences and effects of different ways of crowdsourcing task design in idea selection process. We aim to answer the call for a deeper understanding of crowd evaluation from convergence process perspective. We hope to gain valuable insights into the relationships and interactions between task complexity, idea presentation, and instructional guidance on perceived intrinsic, extraneous, and germane cognitive load as well as on convergence quality and satisfaction.

This research will contribute to the research field of cognitive load theory proposed and widely investigated by educational psychology researchers (Liu et al., 2012; Tabbers et al., 2004). To our knowledge, cognitive load theory have not yet been systematically applied and tested in the research of IT enabled crowd behaviors. Through the grouping of experiment conditions and the consideration of corresponding control variables, our research may offer insights into the interaction mechanisms of different types of cognitive load, and help better understand individuals' cognitive load variations in different environments.

Practically, our findings could inform the design of crowdsourcing processes and platforms to support the convergence activity between idea generation and idea selection. The results will offer suggestions on the process design for the tradeoff between convergence quality and individual satisfaction. The studied interventions could be helpful for real word shortlist crowds to make convergence more effective. Our study will also have implications for small group researchers that are studying similar processes in a face-to-face setting.

Appendix

Below are the instruments to measure the variables. Some questions are adjusted to our study's context. A seven-point Likert scale will be used for all questionnaires (1 = strongly disagree; 7 = strongly agree).

Intrinsic Cognitive Load (α>0.7 (Chang et al., 2017))
1. The task is difficult. 2. The task is complex. 3. The task is not easy to comprehend. 4. The task is beyond my competence.
Extraneous Cognitive Load (α>0.7 (Chang et al., 2017))
1.I do not like the presentation or organization of the ideas. 2. I am not comfortable with the presentation or organization of the ideas. 3. The presentation or organization of the ideas requires strenuous efforts when processing them. 4. The presentation or organization of the ideas is not helpful for me to process.
Germane Cognitive Load (α=0.91 (Cheon & Grant, 2012))
1. The guidance contributed to my processing of the ideas. 2. The guidance helped me to mentally organize the idea processing. 3. The guidance really enhanced my deliberation of the ideas. 4. As we progressed throughout the activities, the guidance helped me to concentrate on the processing of

the ideas. 5. While proceeding throughout the activities, the guidance helped me to better complete my task. 6. The guidance makes it easy for me to do similar tasks again.
Satisfaction with Process (α=0.85 (Briggs et al., 2013))
1. I feel good about today's idea processing. 2. I liked the way the activities progressed today. 3. I feel satisfied with the procedures used in processing the ideas. 4. I feel satisfied about the way I carried out the idea processing.
Satisfaction with Outcome (α=0.92 (Briggs et al., 2013))
1. I liked the outcome. 2. When the idea processing was over, I felt satisfied with the results. 3. My accomplishments today give me a feeling of satisfaction. 4. I am happy with the results of today's idea processing.
Knowledge Self-Efficacy (α=0.86 (Lin, 2006))
1. I am confident that the ideas that I picked from the original set were of the highest quality. 2. While selecting ideas, I felt like I had the necessary knowledge and competency to identify good ideas. 3. While selecting ideas, I did not think I could pick the most promising ideas. 4. Most other people are better at picking promising ideas than I am.
Need for cognition (α=0.87 (Tam & Ho, 2005))
1. I try to avoid situations that require thinking in-depth about something. 2. I prefer complex problems to simple problems. 3. I don't like to have to do a lot of thinking. 4. Thinking hard and for a long time about something gives me little satisfaction.
Manipulation check
1. Taken as a whole, how difficult was the task you have finished? 2. Taken as a whole, how clear was the information being presented? 3. Taken as a whole, how useful was the guidance given in the task?

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